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# Moving objects detection based on kernel independent component analysis

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**Abstract**

In video moving objects detection, the same illumination and perspective, will lead to that moving objects and background is nonlinearly mixed. In this paper, Kernel Independent Component Analysis (KICA) algorithm is proposed to detect the video moving objects. By the selection of kernel's parameters, the proposed algorithm avoids the unreasonable assumption which moving objects image and background image is completely independent in the video moving objects detection based on the Independent Component Analysis (ICA). And it achieves the separation of moving objects and background in the feature space by kernel function. Experimental results demonstrate that KICA is better than ICA in video motion detection.


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*Key Words:* Kernel Independent Component Analysis; Kernel methods; Moving Objects Detection

## 1. Introduction

Moving objects detection is to extract moving objects in video image sequences. It's a basic step of target tracking, target classification and behavior understanding. Many researchers have been studying about this issue and many algorithms of moving objects detection are proposed, such as Background Subtraction [1], Frame difference [2] and so on. Either Background subtraction or Frame difference method is hindered by the illumination change in the scene.

Independent Component Analysis (ICA) [3] is a new algorithm for blind source separation. The image sequences of video are considered as the mixed signal of statistically independent moving objects

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component and background component. By using ICA algorithm, a decomposition matrix is found to detect moving objects from the sequences. In fact, moving objects image and background image are not completely independent for the same illumination and perspective. Therefore, Tsai and Lai [4] proposed to improve the detection result by limiting the iterations of independent component decomposition.

Kernel Independent Component Analysis (KICA) [5] is a nonlinear ICA algorithm. It maps signals into a high dimensional feature space by the kernel method which is a nonlinear function in Reproducing kernel Hilbert space (RKHS). In the high dimensional feature space, the minimization of the contrast function achieves the decomposition of the independence components. In this paper, KICA is applied to video moving objects detection. Comparing the ICA, KICA can better address the non-linear mixed problem of the moving objects image and the background image.

## 2. Algorithm and Implementation

### 2.1. ICA

For $m \times n$ video image sequences, its image is seen as the mixing image of the background and moving objects. And every image can be re-arranged into a $N$ dimensional column vector, where $N = m \times n$ . This can be expressed as:

$$\mathbf{Y} = \mathbf{AS} \tag{1}$$

where $\mathbf{S} = [\mathbf{s}_b, \mathbf{s}_f]^T$ , $\mathbf{s}_b = [s_{b1}, s_{b2}, ..., s_{bN}]^T$ denotes the background vector, $\mathbf{s}_f = [s_{f1}, s_{f2}, ..., s_{fN}]^T$ denotes moving objects vector. $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2]^T$ , $\mathbf{y}_1$ and $\mathbf{y}_2$ denote two observation vectors, $\mathbf{A}$ denotes the $2 \times 2$ mixing coefficient matrix.

Under the assumption that moving objects and background is independent, moving objects can be detected from the images by ICA. The de-mixing matrix $\mathbf{W}$ is calculated by minimizing the contrast function of the higher order statistics or the approximate entropy. The estimation of $\mathbf{S}$ is $\mathbf{X} = \mathbf{WY}$ , where $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2]^T$ and $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2]^T$ is a $2 \times 2$ de-mixing matrix. Generally, the de-mixing vector with two opposite signs elements is selected for moving objects detection.

### 2.2. KICA

As ICA, the observation data $\mathbf{Y}$ is firstly centralized and whiten. The data is centralizing by:

$$\mathbf{y}_i^c = \left(\mathbf{y}_i - \bar{\mathbf{y}}_i\right) / \sqrt{D_i} \tag{2}$$

where $\bar{\mathbf{y}}_i$ denotes the mean value and $\sqrt{D_i}$ is the variance, $i$=1, 2.

Data whitening is formula as:

$$\mathbf{Y}^W = \tilde{\mathbf{W}}\mathbf{Y}^c = \mathbf{\Lambda}^{-1/2}\mathbf{V}^T\mathbf{Y}^c \tag{3}$$

where the whitening matrix $\tilde{\mathbf{W}} = \mathbf{\Lambda}^{-1/2}\mathbf{V}^T$ . $\mathbf{Y}^c = [\mathbf{y}_1^c, \mathbf{y}_2^c]^T$ . $\mathbf{\Lambda}$ and $\mathbf{V}$ are the Eigen values matrix and eigenvectors matrix of covariance matrix $\mathbf{M}$ respectively, where $\mathbf{M} = \mathbf{Y}^c\mathbf{Y}^{cT}$ and $\mathbf{MV} = \mathbf{V\Lambda}$ .

After the whitening process, KICA is to map the estimation data $\mathbf{X}=\mathbf{W}\mathbf{Y}^{W}$ into an implicit feature space $F$, that $\Phi:\mathbf{x}\in R^{N}\rightarrow\Phi(\mathbf{x})\in F$. Through defining an empirical contrast function, $\mathbf{W}$ is updated by steepest descent method on a Stiefel manifold.

$$C(\mathbf{W})=-\frac{1}{2}\log\lambda_{F}^{K} \tag{4}$$

where $\lambda_{F}^{K}$ is the minimal generalized eigenvalue of $\mathbf{C}\xi=\lambda\mathbf{D}\xi$, $\xi$ is the generalized eigen vector, $\mathbf{C}$ is the covariance matrix of $\mathbf{X}=[\mathbf{x}_1,\mathbf{x}_2]^{T}$ and $\mathbf{D}$ is the block-diagonal matrix of covariances of the individual vectors $\mathbf{x}_i, i=1,2$.

In this paper, kernelization of canonical correlation analysis is used to optimize the empirical contrast function of KICA. Kernelization of canonical correlation analysis can reflect the whole correlation between two sets of indicators using the correlation of integrated variables. Its basic principle is to extract two representative integrated variables $\boldsymbol{\alpha}_1^{T}\mathbf{K}_1$ and $\boldsymbol{\alpha}_2^{T}\mathbf{K}_2$ whose correlation can reflect the whole correlation. Here $\mathbf{K}_1=\left[\left\langle\mathbf{\Phi}\left(\mathbf{x}_1^{i}\right),\mathbf{\Phi}\left(\mathbf{x}_1^{j}\right)\right\rangle\right]$ and $\mathbf{K}_2=\left[\left\langle\mathbf{\Phi}\left(\mathbf{x}_2^{i}\right),\mathbf{\Phi}\left(\mathbf{x}_2^{j}\right)\right\rangle\right]$.

The first canonical correlation is defined by:

$$\rho_F=\max_{\boldsymbol{\alpha}_1,\boldsymbol{\alpha}_2\in R^{N}}\frac{\boldsymbol{\alpha}_1^{T}\mathbf{K}_1\mathbf{K}_2\boldsymbol{\alpha}_2}{\left(\boldsymbol{\alpha}_1^{T}\mathbf{C}_{11}\boldsymbol{\alpha}_1\right)^{1/2}\left(\boldsymbol{\alpha}_2^{T}\mathbf{C}_{22}\boldsymbol{\alpha}_2\right)^{1/2}} \tag{5}$$

where $\mathbf{C}_{11}=\left(\mathbf{K}_1+\frac{Nk}{2}\cdot\mathbf{I}\right)^{2}$ and $\mathbf{C}_{22}=\left(\mathbf{K}_2+\frac{Nk}{2}\cdot\mathbf{I}\right)^{2}$, $k$ is the regularized estimator.

To ensure the uniqueness of canonical variables, set $\boldsymbol{\alpha}_1^{T}\mathbf{C}_{11}\boldsymbol{\alpha}_1=1$ and $\boldsymbol{\alpha}_2^{T}\mathbf{C}_{22}\boldsymbol{\alpha}_2=1$. So Lagrange multipliers are used to solve the maximization of the first canonical correlation and obtain the optimal $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$, the result is as follows:

$$\begin{cases}\left(\mathbf{C}_{11}^{-1}\mathbf{K}_1\mathbf{K}_2\mathbf{C}_{22}^{-1}\mathbf{K}_2\mathbf{K}_1-\rho_F^{2}\right)\boldsymbol{\alpha}_1=0\\ \left(\mathbf{C}_{22}^{-1}\mathbf{K}_2\mathbf{K}_1\mathbf{C}_{11}^{-1}\mathbf{K}_1\mathbf{K}_2-\rho_F^{2}\right)\boldsymbol{\alpha}_2=0\end{cases} \tag{6}$$

where $\rho_F^{2}$ is the maximum eigenvalue and $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$ are the corresponding eigenvectors. The relationship of the minimal generalized eigenvalue and the first canonical correlation is $\lambda_F^{K}$=1-$\rho_F$ [5].

The de-mixing matrix $\mathbf{W}$ is updated by

$$\mathbf{W}_{n+1}=\mathbf{W}_n\exp\left(\beta\left(\mathbf{W}_n^{T}\mathbf{H}-\mathbf{H}^{T}\mathbf{W}_n\right)/2\right) \tag{7}$$

Where $\mathbf{H}=\frac{\partial\mathbf{C}}{\partial\mathbf{W}_n}-\mathbf{W}_n\left(\frac{\partial\mathbf{C}}{\partial\mathbf{W}_n}\right)^{T}\mathbf{W}_n$, scalar $\beta$ is detemined by Golden search. When $\mathbf{W}_n$ is convergence, the process of iterative optimization will cease.

*2.3. Parameters Problem*

For KICA based on the Gaussian kernel, two parameters need to be set: the width $\sigma^2$ of the kernel which controls the radical scope and the regularized estimator $k$ which can center points in feature space. Along with $\sigma^2$ approaching zero or infinity, every element in $\mathbf{K}_1$ and $\mathbf{K}_2$ tends to one or zero. $k$ will influence the effect of features variances and features correlation coefficients. So the value of $\sigma^2$ and $k$ should be chosen carefully.

## 3. Experimental Results

To verify the effectiveness of the algorithm, we select an indoor scene whose illumination is affected by light and sunshine through the window. In this scene, a 240×320 video with the frame rate of 10 frames per second is recorded to test the capability of moving objects detection of this algorithm under the condition of illumination change.

### *3.1. Selection of parameters*

In practice, moving objects can't be completely accurately detected. In order to quantify the performance difference of different parameters, two kinds of detection performance indicators, detection rate (R) and similarity (S), are used to measure the results of various parameters, which are calculated as follows:

$$\mathrm{R} = \frac{tp}{tp + fn}, \quad \mathrm{S} = \frac{tp}{tp + fn + fp} \tag{8}$$

Where $tp$ and $fn$ are the numbers of correct pixels and false pixels, $fp$ is the number of missed pixels.

To segment moving objects in the estimated image, an adaptive threshold is used to binarize the image. The threshold is $thres = m_0 + l \cdot \mathrm{var}_0$, where $m_0$ and $\mathrm{var}_0$ are respectively the mean and standard deviation of the estimated image.

According to R and S in the following table, with the decreasing $k$, the number of pixels correctly detected is increasing and the performance is better. The table also shows the influence of the width of Gaussian kernel $\sigma^2$. When $k$ is small and $\sigma^2$ is increasing, R and S first increased and then decreased to denote that there is an extreme value of $\sigma^2$ which makes the performance better. To sum up, $k$ should be small, and $\sigma^2$ should be the extreme value. Here the best choice is $k$=0.002 and $\sigma^2$=0.25.

Table 1. Influence of various parameters ( $l = 1.5$ )

| $\sigma^2$ | 0.1 | | 0.25 | | 0.5 | | 1 | | 2.5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| k | R | S | R | S | R | S | R | S | R | S |
| 0.002 | 0.7680 | 0.7636 | 0.7760 | 0.7727 | 0.7757 | 0.7723 | 0.7545 | 0.7507 | 0.7378 | 0.7347 |
| 0.02 | 0.7452 | 0.7418 | 0.7519 | 0.7484 | 0.7549 | 0.7517 | 0.7437 | 0.7403 | 0.6939 | 0.6904 |
| 0.2 | 0.6513 | 0.6481 | 0.6238 | 0.6203 | 0.5987 | 0.5948 | 0.6527 | 0.6495 | 0.7017 | 0.6982 |

### *3.2. Comparison between KICA and ICA algorithm*

With different illumination, FastICA [6] is used as the comparison algorithm of KICA algorithm. Their experiment results are as follows:

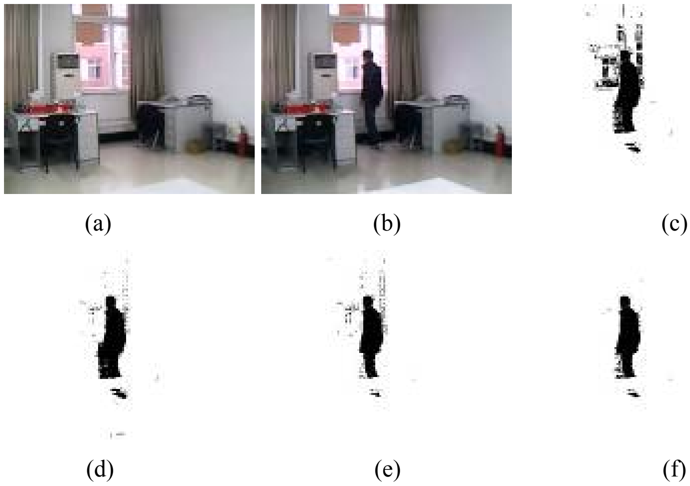

Fig. 1. (a) reference background image; (b) the image containing a person; (c) binary result in FastICA algorithm with $l = 1.5$ ( R=0.5305, S=0.5258); (d)binary result in KICA algorithm with $l = 1.5$ ; (e) binary result in FastICA algorithm with $l = 2$ ( R=0.8027, S=0.7749); (f) binary result in KICA algorithm with $l = 2$

From the binary results of covered images and values of R and S, it can be seen that extracting moving objects in ICA algorithm performs worse than in KICA. It is decided by the good property of the contrast function constructed after mapping data into a high dimensional in KICA algorithm.

## 4. Conclusion

In the process of moving objects detection, the correlation between the moving objects image and background image makes the detection performance of ICA is not satisfactory. KICA is to map the data into an implicit feature space, and kernelization of canonical correlation analysis is used to optimize the empirical contrast function of KICA. Compared with ICA algorithm, it’s better to segment moving objects from video by KICA algorithm in the condition of illumination change.

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